Individual Differences in Information Processing in Networked Decision Making

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ABSTRACT: *In today's networks, individuals frequently face the problem of information overload. The amount of information available for a decision is often much larger than a person can process to make an informed decision. Past research has shown that individuals can differ significantly in how they use information in making decisions. Individuals may differ in their willingness to seek and incorporate more information into their decision making, some relying more on information at hand than simple heuristics. Individuals' desire to reach a closure quickly by making a decision may differ as well, depending on situational factors such as the level of inherent ambiguity or uncertainty in the decision. These factors have not yet been studied deeply in the context of networked information processing in terms of their impact on the timeliness and accuracy of decisions. In this paper, we address this problem by introducing an agent-based model that incorporates four characteristics representing individual differences: competence, engagement, decisiveness and reliance on neighbors' opinions for corroboration. Based on a novel way of modeling the degree of problem difficulty, we investigate the impact of individual differences in networked decision making through comprehensive simulation experiments. Our simulation results show that being more engaged with a task does not always improve team performance and can lead to information overload if it is coupled with high information push activity. Similarly, heuristic decisions as a result of high decisiveness can be useful in various problem settings and can be further improved by a small amount of corroboration.*

1. Introduction

In today's networks, individuals frequently face the problem of information overload: the amount of information available for a decision far exceeds the capacity of individuals to process information. However, individuals also differ in their motivations for seeking and engaging with information. *Need-for-cognition* (NC) [Cacioppo et al., 1982] refers to an individual's desire to seek relevant information and integrate evidence to reach a conclusion. On the other hand, *need-for-cognitive-closure* (NCC) [Webster and Kruglanski, 1994] indicates the desire to arrive at a decision quickly to avoid discomfort caused by ambiguity or uncertainty. It has been shown that the individual differences in NC and NCC play a significant role in information sharing [Henningsen and Henningsen, 2004] and the influence one may have over others in the network [Marsden and Friedkin, 1993]. While agents models have incorporated the notion of bounded rationality [Carley et al., 2009], the impact of individual differences especially in the NC and NCC scales on accuracy and timeliness of decision making has not been studied deeply in the literature.

In this paper, we introduce an agent-based model for decision making in which individuals share facts with each other and make decisions based on information at hand in a networked environment. We manipulate

two significant aspects of the simulation: the characteristics of individual agents based on the NC and NCC scales and the overall problem difficulty. And then we investigate how these factors impact both the timeliness and the accuracy of decision making. The model proposed in this paper expands on our prior agent-based model [Chan et al., 2013], [Chan and Adalı, 2012] with three new measures of an individual's differences: engagement, corroboration threshold and decisiveness. While engagement is related to NC scale, corroboration threshold, and decisiveness are models of the different components of the NCC scale. In addition, we use the agent competence model from our prior work to arrive at four interrelated individual difference parameters.

We conduct an agent-based simulation study in which agents share information with the intention to make an informed decision. We introduce a novel way of modeling problem difficulty in terms of facts that contain arguments in support of making a decision (*pro*) and arguments against the same decision (*con*). Furthermore, we consider information that is useless (i.e., noise) but can cause confusion if interpreted as valuable due to lack of expertise. Our simulation scenario allows agents to make heuristic decisions when only little information is available about the given task and more informed decisions can be made upon receiving more of the available information. By changing the distribution of facts along with the two dimensions of type of evidence (i.e., *pro* vs. *con*) and benefit (i.e., *valuable* vs. *noise*), we manipulate the underlying difficulty of the problem. The more difficult a problem is, the higher the risk of making an incorrect decision with limited information and in the presence of information processing errors.

Using this novel model, we study how individual differences impact the timeliness and accuracy of decision making. We demonstrate that being more engaged with a task by processing and sending out information to the network does not always improve team performance and can lead to information overload. This type of engagement results in noisy information being multiplied in the network faster than the network's ability to filter it out. Similarly, higher decisiveness modeled as reliance on smaller set of facts can be more robust to this type of information overload in some situations. Interestingly, corroboration coupled with high decisiveness results in best performance overall, by making quick decisions and then reducing the overall noise in the network quickly by routing only information that supports a given decision.

2. Related Work

There is a great deal of work on factors relating to information sharing behavior in terms individual or social motivations. In trust literature, the focus is on understanding how individuals trust others as sources of information for decision making [Fiske et al., 2007]. Often the competence of others and their reliability are prominent factors. In information processing, individuals also concentrate on factors that relate to the properties of the information itself [Hilligoss and Rieh, 2008] that signal whether a piece of information is likely to be true based on heuristic factors such as the presentation of the information and the confidence of the source. In particular, the information consumer integrates these multiple concerns to derive the credibility of the information as well as the trust for the source depending on the decision context [Adalı, 2013]. If the information consumer has sufficient cognitive resources and expertise in the problem domain, they are more likely to process information in an effortful manner and rely on their own judgment. In other cases, they are more likely to rely on the surface cues of the information itself or on the trust for the sources. Some agent-based models have incorporated the trust aspect of information processing into networked decision making situations [Chan et al., 2013], [Thunholm et al., 2009]. In particular, the taNdem (A Trust-based Agent framework for Networked DEcision Making) agent simulation system [Chan et al., 2013] is the first to explicitly model the competence and willingness of agents as well as the trust beliefs for the competence and willingness of other agents. However, the taNdem does not consider the individual differences of agents in information processing behavior as well as the underlying difficulty of the problem being solved, which is the focus of this paper. Other work has concentrated on the influence of opinion leaders and beliefs of individuals in settings with agents with bounded processing capacity [Carley et al., 2009]. In this paper, we do not incorporate prior beliefs and social influence to the model, but leave these to our future work.

An additional line of work considers an individual's information seeking behavior in an information pull scenario. The main problem is to understand how individuals choose to query sources, what keywords they use and which sources they select [Case, 2008]. Some information models study how individuals' understanding of the problem domain evolve over time based on the information they process [Pirolli and Fu, 2003]. They use a brain activation model that shows how people build a mental model of the problem space. On the other hand, other models aim to understand how the underlying tasks, the awareness of existing information and the outcomes of different information seeking actions predict the future actions of individuals [Leckie, 2005],

[Wilson, 2005]. In this line of work, the models need to balance situational factors, such as availability of information, with personal factors such as the desire to seek information [Ingwersen and Jarvelin, 2005].

Two types of individual differences play a significant role in these information models: the need for cognition (NC) [Cacioppo et al., 1982] and the need for cognitive closure (NCC) [Webster and Kruglanski, 1994]. An individual with high NC tends to engage more with information, processing more and basing her decisions on the gathered information [Cacioppo et al., 1982]. An individual with low NC tends to take a heuristic approach in information processing and to make decisions based on it such as fluency of information (i.e., presentation of information). The NCC scale [Webster and Kruglanski, 1994] deals with the desire of an individual to quickly reach closure by making a decision. An individual with high NCC tends to make faster decisions while an individual with low NCC can delay decisions. While these two measures are correlated [Kossowska and Bar-Tal, 2013], NCC is more complex integrating five different personality aspects: *preference for order, predictability, decisiveness, discomfort with ambiguity* and *closed-mindedness*. Hence, delaying a decision may not necessarily be a result of the desire to process more information as in NC, but for a desire to resolve ambiguity of the underlying decision. Furthermore, it has been shown that the individual components of the NCC scale remain the same across multiple cultures [Mannetti et al., 2002].

Despite the importance of these two factors (NC and NCC) in determining how individuals process information, there is little work in understanding how these factors interact in networked decision making scenarios in which teams often have to deal with information overload. To the best of our knowledge, this paper is the first to investigate their impact on networked teams.

3. Agent-based Model

In the paper, we consider an agent-based model where agents are connected to each other through an undirected network which could model either a communication network connectivity, a social network ties or organizational role based relationships. Individuals communicate with all their neighbors in the network at all simulation steps to accomplish a task. We leave the impact of prior or task specific trust which would lead to changing communication partners throughout the simulation to future work. Agents in the simulation exchange information to help each other make a decision. Each unique piece of information is called a *factoid*. In the information sharing scenario we consider, a fixed number of factoids are distributed to all the agents' inbox in the beginning of the simulation, and diffuse to other agents throughout the simulation.

At each step of the simulation, each agent processes some of the factoids from its inbox. For each factoid they process, they make a determination on whether the factoid contains valuable information or not. If the agent thinks the factoid is valuable, it will first put this factoid in its knowledge base and immediately send the factoid to all its neighbors in the network. Agents will not send the same factoid out more than once. However, an agent may receive and process the same factoid multiple times as it arrives from different neighbors as long as it is not yet in its knowledge base. In other words, if the agent did not think a fact was valuable the first time it has seen it, it may do so upon receiving it multiple times. The new factoids received from neighbors will accumulate at the top of the inbox of each agent at the end of each simulation step.

This simulation scenario is very similar to ones proposed in prior work [Chan et al., 2013], [Thunholm et al., 2009] with a few differences. First, the fact that new information accumulates on top of the inbox models the reality of many information push scenarios such as micro-blogs or an inbox sorted by recency. As another new addition, agents will make decisions as soon as they think that they have processed sufficient number of factoids. The decisions are based on the amount of knowledge available in this model, but not a time deadline. This choice allows us to investigate how other simulation factors impact both the timeliness and the correctness of decisions.

Once an agent makes a decision, it continues to share factoids with other neighbors, but now it only shares factoids that it thinks as valuable and supports the current decision. This allows agents to influence other agents' decisions by selective sharing. Agents may change their decisions as more facts become available in the simulation. In our model, an agent's behavior is only influenced by the personal (nodal) characteristics, not by edge characteristics like trust (e.g., trust relationships with communication partners). We leave this aspect of investigation for our future work.

3.1 Modeling of Decision Tasks

To enable the agents to make decisions, the factoids corresponding to a task are divided into four types.

The *benefit* of factoids differs between valuable and noise. A valuable factoid is evidence relevant to decision making. A noisy factoid (or noise) is information that should be disregarded completely in an ideal scenario. However, agents may make errors in detecting usefulness

Algorithm 1 Agent Behavior

```
function AGENTBEHAVIOR(a)
    Input: an agent a with engagement e, decisiveness d, competence c and corroboration factor cf
    pro_facts = 0, con_facts = 0
    for all facts f in a's current knowledge do
        if the fact has been sent by x neighbors where x >= cf then
            pro_facts+ = x if the fact is pro decision, con_facts+ = x otherwise
        end if
    end for
    if |f| >= max(1, (1 − d) * (x_1 + x_2)) then          ▷ x_1/x_2 max number of pro/con facts
        Make a PRO decision if pro_facts > con_facts and CON decision otherwise
    end if
    for C * e times do                                     ▷ (C is max capacity for all agents)
        Pick a factoid f from inbox of a
        if f is not in a's knowledge then
            val is the correct value of f by probability c, reverse otherwise
            If val = False but f is sent by >= cf neighbors, then val = True
            if val then                                    ▷ a thinks f is valuable
                add f to a's knowledge
                if a has not made a decision or f agrees with a's decision then
                    Put f on the top of the inbox of all a's neighbors
                end if
            end if
        end if
    end for
end function
```

of the evidence and judge a valuable factoid as noise (i.e., false positives), and a noisy factoid as valuable (i.e., false negatives). These errors lead to using incorrect information in decisions and increased noise in the network.

The *evidence* of a factoid can be *Pro* or *Con*. *Pro factoids* are arguments supporting a decision, and *Con factoids* are arguments against the decision. Agents do not make errors regarding the evidential value of a factoid, whether a factoid is for or against a decision. If a fact is Pro, it will always be known correctly as Pro, or vice-versa.

The ground truth of a fact is either Pro Valuable (PV), Pro Noise (PN), Con Valuable (CV) and Con Noise (CN). Each decision task is supported by a number of factoids of different types. We will use the representation $[V : (x_1/x_2), N : (y_1/y_2)]$ to represent the number of facts with ground truth PV (x_1) and CV (x_2), and PN (y_1) and CN (y_2). The correct decision for the agent should be Pro if $x_1 > x_2$ and Con, otherwise.

As agents are bounded, they do not have access to all the facts and to the ground truth for the facts. Without global view based on perfect knowledge, all the agents make decisions based on their own knowledge base at a given point in time which contains the factoids they perceive valuable. We represent the knowledge base of an agent at some point t in the simulation with $[(z_1/z_2)]$ where z_1 is the number of Pro factoids and z_2 is the number of Con factoids the agent has processed and perceives as valuable at time t (including those identified in error). An agent will make a *Pro* decision if $z_1 > z_2$ and a *Con* decision otherwise.

The distribution of factoids along the four dimensions represents the inherent difficulty of a decision. Suppose we have $[V : (50/25), N : (10/10)]$. This is an easy decision because there is overwhelming evidence in support of the decision and very little noise. Even if an agent has a small subset of the factoids available, it is very likely that it will have a higher number of Pro factoids than Con factoids, resulting in a correct decision. This is true even if the agent does not correctly identify the value of some subset of factoids. In this case, waiting to process more factoids is not likely to improve the decision accuracy.

A more difficult decision setting could be given by $[V : (50/25), N : (10/100)]$. As there is more noise

than valuable factoids, the agents must not misidentify valuable information and filter it out. Also, they must not make errors regarding the many Con noise factoids and use them as valid evidence against the decision. In short, even a small tendency to make errors can result in incorrect final decisions due to multiplied noise in the network and loss of valuable information.

To summarize, there is a big risk of making a wrong decision if $x_1 > x_2$ but $y_2 >> y_1$ and $y_2 >> x_1$. In other words, if there is a lot of Con noise (y_2) compared to pro valuable facts, then even a small percentage of error can lead to incorrect decisions. Note that if $y_2 >> x_1$ and $y_2 \approx y_1$, the risk is reduced because agents now can make equal mistakes for both Con and Pro noise. Even though the decisions are more random, the risk of errors is reduced.

3.2 Modeling Agent Characteristics

The behavior of each agent is a function of its personal characteristics modeled by four distinct parameters: competence (c), engagement (e), corroboration factor (cf), and decisiveness (d). We can manipulate the characteristics of all the agents in the simulation, or a subset of them. Each agent is cognitively limited, they can process at most C factoids in a single simulation step and can only make decisions based on the information available.

Competence (c) models the task specific expertise of an agent (between 0 and 1). An agent with a competence value of c will correctly identify the benefit of a fact (valuable or noise) with probability c. When $c = 1$, the agent will always identify a fact correctly. The evidence type is always correctly processed, regardless of the competence level.

Engagement (e) models the level of engagement of an agent with the decision making task (between 0 and 1). An agent with engagement e will process $C \times e$ facts from its inbox at each simulation step, with $e = 1$ representing full engagement. Engagement controls how much information is incorporated into decisions and models NC.

Corroboration factor (cf) models an agent's reliance on the corroboration of facts by others for decision making (integer value 1 or higher). This parameter has an effect both in processing of facts and in decision time. When processing a fact with $cf > 1$, the agent will find a factoid valuable if it is sent by at least cf agents at decision time regardless of its own opinion. When $cf = 1$, the agent only relies on its own evaluation of the factoid. High cf values can be a reliable signal of the benefit of facts when agents have a competence of 0.5 or higher, but it may take many simulation steps for an agent to observe a high cf value.

Decisiveness (d) models how many facts the agent needs to have seen (regardless of their perceived benefit) before making a decision (between 0 and 1). An agent with decisiveness of d will need to have seen at least $(x_1 + x_2) \times (1 - d)$ factoids before making a decision. A decisiveness of 0.2 means that the agent must have seen at least 80% of the $(x_1 + x_2)$ factoids. Hence, low decisiveness threshold means that agents need to see a lot of facts and will make decisions more slowly.

Agents make a decision after meeting the decisiveness threshold. At this point, they base their decision on the facts in their knowledge base that have passed the corroboration threshold. In essence, agents can change their mind in two ways. First, a factoid they perceived as noise may eventually be put in their knowledge base if it is seen cf times. Secondly, a factoid that was considered valuable may eventually be disregarded at decision time if it has not met the cf threshold. Once an agent makes a decision, they send only facts that support their decision. Both corroboration factor and decisiveness model various aspects of the NCC scale.

The details of the agent actions and its dependence on the given agent characteristics are given in Algorithm 1.

4. Experimental Setup

Given the model described in Section 3, we run a number of experiments to understand the impact of different factors in team performance. We use the following performance metrics to evaluate our model:

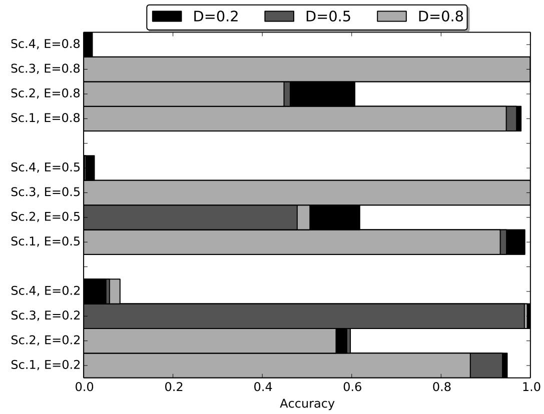
Correct decisions: total number of agents (out of 20) making a correct decision at the end of the simulation.

Accuracy: percentage of decisions that are correct at the end of the simulation with accuracy of 1 representing 100% of correct decisions. In our settings, the PRO decision is always the correct decision without loss of generality.

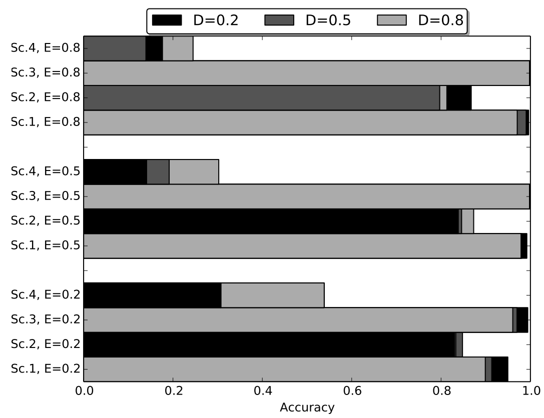
We create a Watts-Strogatz network with 20 agents, each node connected to 3 neighbors with a 0.2 probability of rewriting edges. Then, we seed all the agents with the factoids from the problem space: $P = [(x_1/x_2), (y_1/y_2)]$ where (x_1/x_2) are the number of valuable pro/con factoids, and (y_1/y_2) are the noise pro/con factoids. Each factoid is sent to 3 agents randomly selected in all our experiments. We run each experiment for 10,000 steps and repeat 100 times. In all our tests, the maximum amount of information that can be processed by an agent at a single simulation step is 100 (i.e. $C = 100$).

4.1 Engagement

We first study the impact of engagement. We set the corroboration factor (cf) to 1, forcing agents to



(a) Competence=0.6 (low)



(b) Competence=0.7 (high)

Fig. 1: The impact of engagement and decisiveness on final decision accuracy with different competence values.

only consider their own judgments of factoids' benefit. Intuitively, if an agent is engaged with an activity, they are expected to incorporate more information and make better decisions. To study this hypothesis, we construct 4 different experimental problem settings, given the same total number of facts as shown below.

Scenario	x_1	x_2	y_1	y_2
Sc. 1	50	40	75	75
Sc. 2	50	40	50	100
Sc. 3	50	40	100	50
Sc. 4	50	40	0	150

We run two sets of experiments with low (0.6) and high (0.7) competence as shown in Figure 1. In many scenarios, higher engagement actually reduces the decision accuracy. The reason is that whenever an agent determines that a factoid is valuable erroneously, it copies the factoid to all its neighbors. Hence, noise is multiplied quickly. As a result, if each agent processes a lot of information at once and ends up sending out a lot of noise, the overall noise in the network is suddenly multiplied. Let us now consider a different extreme case. Suppose a single factoid is processed by each agent at each time step. For a noise factoid to be sent from agent 1 to 2, and then 2 to 3, both agents 1 and 2 have to make consecutive errors (by probability 0.3 each). As long as the overall competence of agents is above 0.5, noise is slowly eliminated in network processing. We have illustrated this effect in our previous work [Adalı et al., ress].

Given these two competing factors, the problem space is crucial in determining which one is going to be more dominant. In scenario 4 with a considerable amount of misleading noise (150 CN factoids), even small errors lead to a large amount of noise being multiplied in the network and agents spend all their time filtering this information out. By increasing engagement, filtering is delayed and the overall team effectiveness is reduced. In scenario 2, we see that agents with high decisiveness are impacted negatively from this problem. As information is passed through the network, the agent needs to wait to make a decision, letting the filtering process take place to reduce noise. However, in scenarios 1 and 3, where the noise tends to provide evidence for the correct decision, high engagement allows good decisions to be made quickly and frequently.

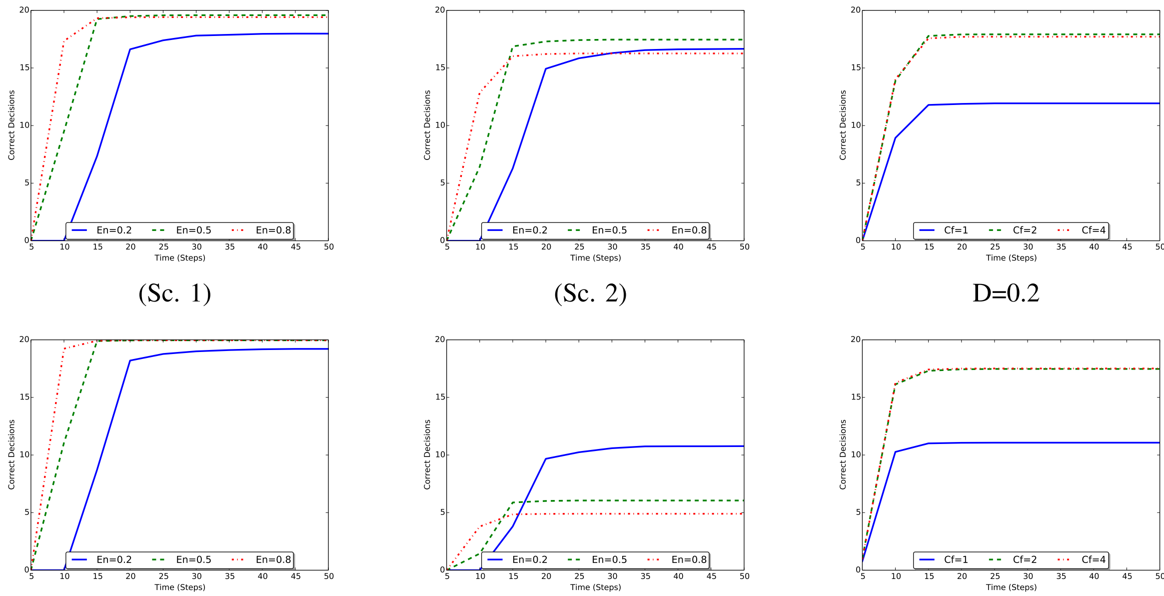
Overall, we can observe increased engagement only helps accuracy in the situations without high quantities of misleading noise. In situations where engagement can cause information overload, lower decisiveness is more beneficial.

Finally, we can verify this finding by looking at the timing of decisions as shown in Figure 2 (a). Each of the four scenarios was run with a competence of 0.7. Higher engagement results in faster but lower accuracy initial decisions. Initial decisions guide the remaining network traffic, resulting in faster convergence to similar decisions for the other nodes. The only case in which this is not true is in Scenario 4 with a lower number of facts and an easier problem scenario.

4.2 Corroboration Factor

In this section, we consider the impact of the corroboration factor in final decision accuracy. For these experiments, we set engagement to 0.8 and consider the two scenarios shown below.

Scenario	x_1	x_2	y_1	y_2	Competence
Easy	50	40	10	100	0.8
Difficult	50	40	50	100	0.6



(Sc. 1) (Sc. 2) D=0.2

(Sc. 3) (Sc. 4) D=0.8

(a) Impact of engagement in different scenarios with competence 0.7.

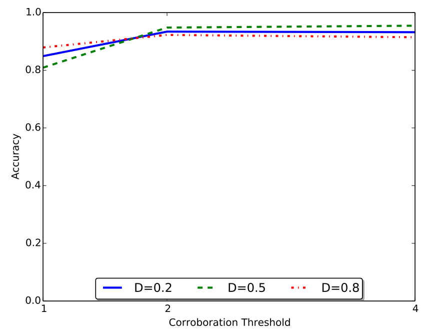
(b) Impact of corroboration on the difficult scenarios with different decisiveness values.

Fig. 2: Impact of engagement (a) and corroboration (b) on the number of correct decisions in different scenarios

Agents' increased reliance on corroboration improves accuracy in two ways. First, in low competence cases, the agent's own opinion alone is too noisy and considering facts corroborated by others helps improve accuracy significantly as it is unlikely for noise to be highly corroborated when competence is above 0.5. Hence in the easy scenario with a competence of 0.8, the improvement due to corroboration is small despite the slightly higher imbalance in the noise. The second effect is due to decisiveness. Higher decisiveness requires fewer factoids, leading to faster decisions. After a decision, agents route only factoids that support their decisions and reduce the overall traffic in the network. High decisiveness with a small amount of corroboration leads to optimal results by increasing accuracy of early decisions and improving overall performance of the network. This quick convergence for high decisiveness (0.8) can be seen in Figure 2 (b). The final decision accuracy is shown in Figure 3. We first note that corroboration improves decision accuracy significantly but there is no significant improvement above a factor of 2 in our problem setting (in which each factor is sent out to 3 agents in the beginning). There is already a significant network effect in filtering noise. Furthermore, the odds of receiving the information 4 times is negligible in our network as each agent is connected to 3 others on average.

5. Conclusions

In this paper, we introduced an agent model for studying the impact of the *need for cognition* and *need for closure* individual difference scales on networked decision making. The proposed model models agents with various characteristics: the competence in distinguishing between noise and valuable information, the decisiveness in terms of being able to make decisions based on few factoids, relying on corroboration to reduce ambiguity and engagement to process multiple facts at each time. We modeled the degree of problem difficulty in a novel way that allows us to study the impact of these differences in realistic information sharing scenarios. Our simulation experiments show that when agents are low in competence, the dependence on corroboration is high. High decisiveness is not always desirable as agents may miss out relevant information while making their decision. Reliance on corroboration with high decisiveness results in an optimal scenario, leading to fast heuristic decision making with high accuracy through corroboration. Higher engagement resulting in higher



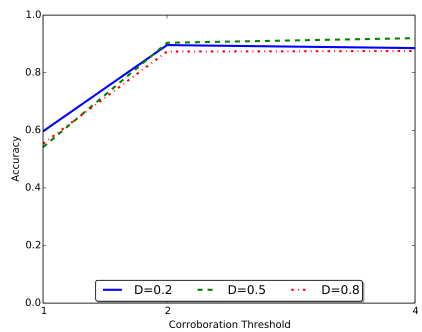


Fig. 3: The impact of corroboration in easy (top) and hard (bottom) problem scenarios.

information processed and sent to the network is not always desirable, reducing the ability of the network to reduce noise through information dissemination paths. This effect is likely to be more intense in denser communication networks. In our future work, we plan to investigate the effects of different network structures, a subset of agents with different characteristics on overall network performance as well as other aspects of the NC and NCC scales such as the desire to stick with one's decisions and open-mindedness on network and team performance.

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